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The Impact using of Artificial Intelligence in Activating Bank Credit: Comparative Analysis

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Abstract: *Artificial Intelligence (AI) in activating bank credit leads to better decision making when analyzing customer data, finding out whether they're credit worthy, saving banks the risks that come with inappropriate credit deploys. AI accelerates the processing of the loan, the accuracy is improved, and the evaluation is fairer. This makes banking credit systems more efficient, customer satisfied, and help to shift public banking credit systems into a smarter and data driven model. This study samples 60 banking professionals from the USA and China having major banks as the basis for the impact of AI on activating bank credit. Research using a comparative approach develops an AI implementation performance by employing credit rate, repayment rate, loss rate, turnover rate and profitability before and after AI implementation. The results of using regression models and ANOVA test confirm that there are significant positive correlations between AI usages and improved banking outcomes. The analysis of key variables such as efficiency, accuracy, profitability and risk management proved that AI stands out as a strong predictor of credit performance. AI brings its results to the assessment of credit, reduces default rates and speeds up the processing of loans.*

Keywords: Artificial Intelligence (AI), bank credit, credit rate, repayment rate, profitability, risk assessment.

INTRODUCTION

Over the recent past, Artificial Intelligence has become a force to reckon with in the financial sector, more specifically in its ability to better credit operations and decision-making processes. Recently, AI technologies like machine learning algorithms, predictive analytics, and natural language processing have become prevalent in all banks in the world for enhanced credit evaluation and minimized risks to operations efficiency (Sadok et al., 2022). The banking sectors of the United States and China are at the forefront of the race for AI integration among the global leaders, having implemented innovative AI solutions to change how credit is awarded, controlled and checked. Based on these observations, this study investigates how artificial intelligence disrupts the process of credit bank activation and compares a top U.S. bank with a top Chinese bank in this regard. It is to assess the effect of AI adoption on the credit rate, repayment rate, loss rate, turnover rate and overall profitability (Purificato et al., 2023). In addition, the research investigates critical evaluation criteria such as the accuracy and efficiency of AI models, as well as their effect on credit risk and financial performance.

With the developments in the financial landscape, banks have to understand how AI is going to help them improve their credit systems' role. USA and Chinese banks together have advanced in AI deployment. There are differences in regulatory environments, technological infrastructures, and customer behaviors, which may lead to different credit-activating and risk-mitigating performances. This study views AI in credit systems from a tangible perspective by performing a before and after analysis of empirical data using AI. The findings will help to expand the small pool of knowledge in the world of financial technology and provide strategic recommendations for banking institutions that may or are debating launching or refinements of AI-based credit operations.

LITERATURE REVIEW

Introduction to Artificial Intelligence in Banking

In the words of Fares et al., (2022), banking is the amalgamation of complex technologies like machine learning, natural language processing, etc., into the sector to effectively carry out banking services through higher level decision-making, automatization of processes and creating better customer experience. AI is of great importance to the financial sector since it is used, especially, for detecting fraud, performing customer service using chatbots or by providing personalized financial advice, as well as for the evaluation and risk assessment in the field of credit (Rahman et al., 2023). Banks can analyze incredibly large dives in real time and draw meaning from them faster and better than ever before with the use of AI. It improves operational efficiency, as well as reduces human error and subsequently provides more informed lending practices.

AI technologies for credit management have evolved to almost a transformative extent. First of all, banks used simple rule-based systems and scores based on historical data and human judgment (Omokhoa et al., 2024). However, in the past, non-traditional data like digital footprints and transaction behavior have been utilized by modern AI systems to derive creditworthiness but only with the advancement of machine learning and predictive analytics. Banks have then been able to extend credit to populations they had previously not been able to and to personalize lending products for improved risk forecasting (Aziz & Andriansyah, 2023). The AI-driven credit management systems are always learning and constantly changing and being dynamic and resilient financial ecosystems is a perfect match for them.

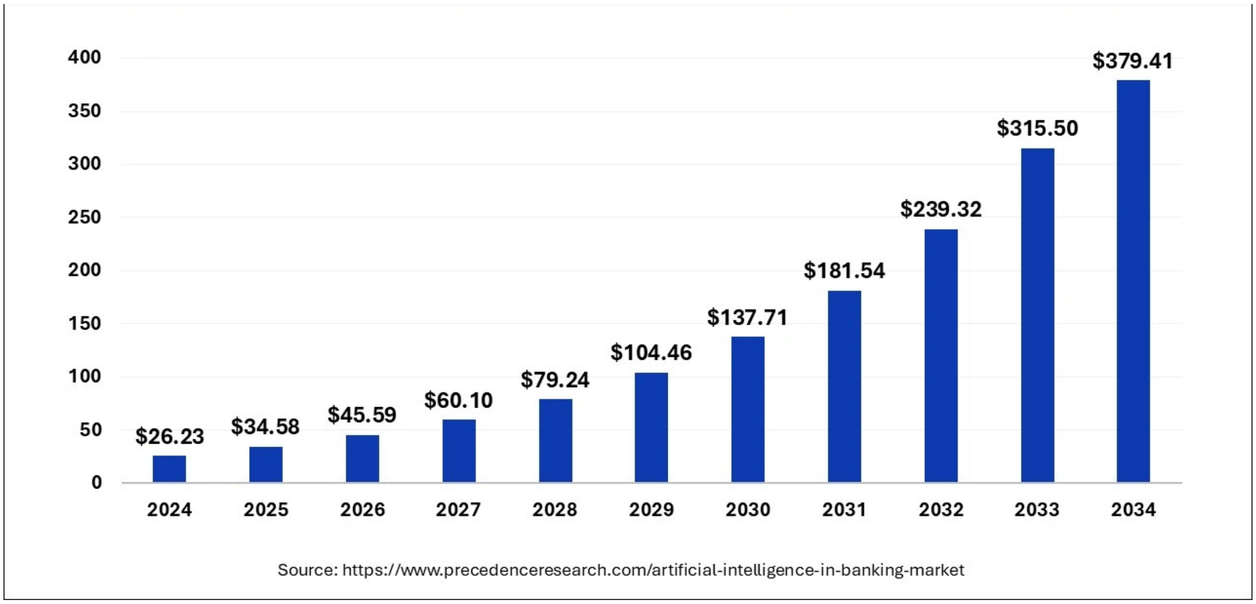

Figure 1: AI in Banking throughout 2024 to 2034

(Source: Precedence Research, 2025)

The Role of AI in Credit Evaluation and Activation

As per the study of Edunjobi & Odejide (2024), banks have adopted Artificial Intelligence technology to evaluate creditworthiness and medieval credit facilities. Machine learning algorithms, neural networks and natural language processing are becoming increasingly common AI tools, which are used to analyze large quantities of structured and particularly unstructured data, including income, employment history, repayment records and to name a few – social media activity, digital footprints, online spending patterns. These tools help banks to create deeper and more accurate pictures of individual or business credit profiles which in turn enable them to more effectively gauge the chance that repayment would occur (Nallakaruppan et al., 2024). Real-time analysis is also possible using AI, with instant decisions of approval for loan and credit limits that decrease processing time and enhance customer experience.

Focusing on the previously mentioned point of difference, AI offers a dynamic and inclusive form of evaluation as opposed to traditional credit evaluation methods. Static financial information such as credit scores and historical loan repayment data lends itself quite heavily to debt verification and infers an entire picture of an individual's financial health may be outright wrong and incomprehensible when it comes to their current state (Cheng et al., 2024). Furthermore, these systems are also often devoid of people with informal credit histories, thus making it inconvenient for various demographics, including young adults or people in developing regions to own credit (De-Lange et al., 2022). However, AI-driven models can intelligently explore alternative data points for availing such as mobile phone usage, utility payment or online transaction history so that banks can assess the creditworthiness from a more complete angle than before.

Impact of AI on Key Banking Performance Indicators

AI integration in the banking sector has been quite transformative for many of the performance indicators, especially in credit-related services. The credit rate, the speed and the degree of closure of loans are probably one of the most immediate influences in the web application of a bank (Al-Ababneh et al., 2023). The traditional loan processing review takes place as static financial documents and manual review, which can lead to delays. However, AI automates the process of evaluating these in real-time using real-time data, predictive analytics and an automated decision-making system. This therefore will enable banks to approve or reject loan applications minutes after loan application, hence increasing the credit rate and making more customers get financial services quicker (Gyau et al., 2024). Not only does this cut down on operation efficiency but it also helps build customer satisfaction and give the organization the competitive edge in the market.

In the words of Elegunde & Shotunde (2020), improvements in the repayment rate of the loans also depend heavily on AI. Using data-driven understanding, banks can weigh in on a borrower’s ability and willingness to pay. The AI algorithms keep watching the borrower's behavior, patterns of income and patterns of getting things spent, down to external factors like market trends, and employment conditions. Therefore, banks can structure loan terms, set reasonable repayment schedules, and notice at-risk accounts. These models can tell the banks when the default is likely to occur, in effect alerting banking to the possibility of restructuring loan terms or providing some financial counseling that will safeguard higher repayment rates. On the other hand, Doumpos et al., (2023) have determined that AI has also been very useful in another area where loss would have been incurred due to non-repayment. Using AI helps banks perform more accurate risk assessments before approving loans using predictive analytics. AI systems rely on previously analyzing huge volumes of both historical and real-time data to determine more reliably who is at greatest risk for failure to perform as expected and then recommend what to do about them. In addition, AI is always learning from previous outcomes and its accuracy gets better and better each time (Jindal, 2024). Rather, there has been a notable decline in the frequency of loan defaults and a decline in the scale of loan defaults, whereby banks' financial losses are minimized and the credit portfolio is made more stable as a whole.

Besides, AI is observed to have a defined impact on the loan turnover rate and the bank's overall profitability. The higher turnover rate that comes as loans are issued repaid and reissued as AI accelerates credit processing and boosts customer targeting. Automating and automating risk assessment helps banks to process more loans faster and with more confidence in repayment. It does make a more fluid lending cycle in which revenue is higher and capital use is maximized. This is at the same time when operational costs become less due to the reduced reliance on manual processes and better allocation of financial resources, thereby increasing profitability (Qasaimeh & Jaradeh, 2022). It makes it easier to price up loans more strategically and assists with discovering the most lucrative customer segments to increase margins.

Accuracy and Efficiency of AI Credit Models

According to Addy et al., (2024), AI credit models are capable of enhancing credit evaluations in terms of accuracy and efficiency as they have become the popular choice in the banking industry. Usually, performance metrics like precision, recall, F1-score, and the area under the ROC curve (AUC-ROC) are employed to appraise these models. In statistics, precision is the fraction of true positives amongst all predictions, i.e. how many of the approved loans truly have not been risked.

This is recall and it will measure the model's ability to identify all actual positive, i.e. all creditworthy applicants. The F1 score takes into consideration both precision and recall with the aim of a comprehensive evaluation, whereas AUC-ROC does provide a means of evaluating the model's general power to separate bad from good credit risk (Wang, 2024). These metrics have high performance meaning that the AI system provides better credit decisions compared to that of humans which translates to more accurate credit decisions for not defaulting by a borrower when they can and making more approvals for the eligible borrowers.

In the words of Faheem (2021), AI algorithms are highly efficient as they save a lot of time and resources in credit assessment. In real-time, this kind of processing of historians' financial records, transaction histories, and behavioral data sounds too impossible to be possible, but it does exist in the form of machine learning models capable of processing very large datasets in seconds to generate credit evaluations. It not only makes the loan approval process quick for the borrower but also cuts operational costs by minimizing manual interaction (Edunjobi & Odejide, 2024). In addition, AI systems can learn continuously, and therefore through improvements to the system as additional data comes to hand, these systems are long-term effective and reliable.

The case of the United States and that of China shows how the AI credit models can be illustrated. Banks such as JPMorgan Chase and Wells Fargo have also made use of the power of AI for approving loans faster and reducing credit fraud. As with most of these models, they often employ a combination of traditional financial data along with utility bills and rent payment histories. At the same time, in China, Ant Financial and China Construction Bank have carried AI integration further by integrating sophisticated deep learning models and big data analytics (Ghimire, 2024). These systems make new kinds of assessments such as e-commerce transaction behavior, social media activity and mobile app usage.

The fact that consumers in China are more mobile-first means they are generally more reliant on the alternative data in use and mobile-driven AI platforms than they are elsewhere in the world. In contrast to this, U.S. banks usually focus on regulatory compliance and combine AI with former practical ones of credit scoring (Bhattacharya & Sinha, 2022). Although the approaches differ, the results are proof that AI credit models do a dramatic job of improving the accuracy and other aspects needed for quick, just, and inclusive lending for diverse markets.

AI and Credit Risk Management

In the modern credit risk management industry, Artificial Intelligence (AI) has become a critical tool that helps banks assess, track and react to financial risks. In the words of Milojević & Redzepagic (2021), AI has one of the best applications in this domain in assessing risk and fraud detection. Due to its ability to assess the high level of accuracy in assessing the creditworthiness of borrowers, AI algorithms can identify patterns in vast amounts of structured and unstructured data such as financial statements, transaction history and behavioral patterns. Unlike historical credit score-driven models, the AI systems use real-time data and being in advanced pattern recognition to find anomalies and signals that can signal potential fraud. In addition, Paramesha et al., (2024) have stated that machine learning and deep learning models continuously learn from both fraudulent and legitimate transactions, becoming progressively good at distinguishing between the two. Through these models, customers whose behavior is even the most subtle but suspicious will be able to be identified, significantly reducing the percentage of false positives so that genuine customers are not inconvenienced. Real-time monitoring and the automated alert system are thus useful for banks to respond instantaneously to assure the overall security of credit systems and protect customer trust.

As per the study of Vesna (2021), minimum default risks are also equally important played by AI. Banks can use predictive analytics to make predictions about the potential default of a current account. Different variables are assessed by AI such as income stability, debt-to-income ratio, repayment history, and even market or regional economic trends to predict a default by a borrower. By adopting this proactive approach, banks can select measures, such as reducing the viability of the default, for example by changing credit restrictions, financial advice or the restructuring of the payment schedule. Additionally, AI makes continuous dynamic credit risk scoring, which reflects the real data and behavior of a borrower in real-time, so that the risk assessment is reliable and up to date. Moreover, Mhlanga (2021) stated that AI helps manage the risk of the portfolio to divide borrowers by risk categories and look for trends in certain demographic or geographical groups. By doing this, banks can make strategic decisions on determining lending policies, capital allotment, and risk mitigation strategies. Finally, the use of AI in credit risk management of banks brings in the capacity to predict fraud more efficiently, take risk measurement more precisely and the rate at which default occurs, thereby ensuring financial stability and responsible lending.

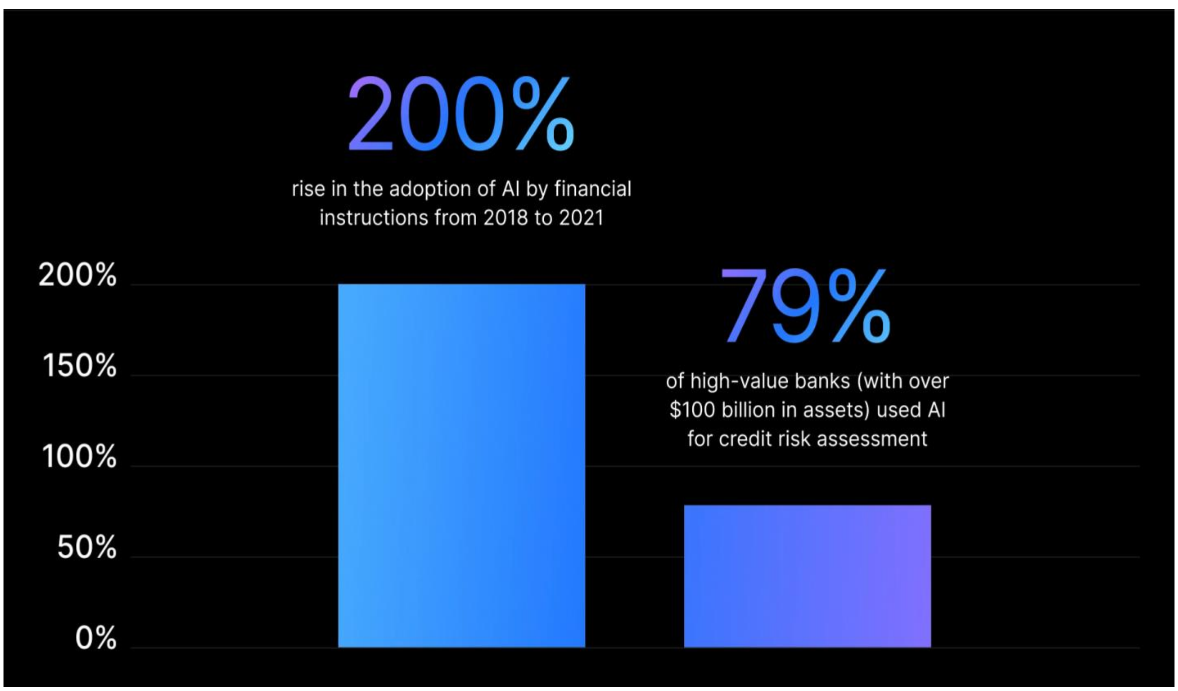

Figure 2: AI in credit risk assessment

(Source: Zavgorodniy, 2025)

METHODOLOGY

Significance of the research

This research has significance due to its potential to offer important information on how Artificial Intelligence (AI) changes how banking sector credit activation processes function. As banks are adopting AI as it gets deployed into the more traditional dimensions of the credit assessment and decision-making components, it is important to understand the actual effects on the core financial indicators which include credit rate, repayment rate, loss rate, turnover rate and profitability. This study compares the before and after implementation of AI to further emphasize how AI can help in improving the accuracy of credits, operational efficiency, risk reduction and in turn bringing profit. In addition, this research will help deepen the understanding of how such models impact risk assessment and the creditworthiness evaluation enhances more knowledge and fairness for the lending practices. The findings can provide a policy and financial institution basis for strategic decisions on investment in AI and credit management framework. The addition of a study like this one to the growing body of knowledge on AI applications in finance helps academia empirically demonstrate the benefits and challenges of AI in the financial realm. In general terms, this research is aimed at filling in a gap in the area of financial innovation, developing smarter data-driven processes for the creation of this smarter, better and safer banking practice.

Research problem

Artificial Intelligence (AI) continues to rapidly integrate into the banking sector but there has not been a comprehensive grasp of the actual effect that the implementation of AI has on the ledger activation processes. Much of the credit evaluation process is inefficient and inaccurate and exposes the institution to higher risk. The result can also be high default rates, low profitability, and other operational problems. As more and more companies engage with AI, they claim that it will help in improving the decision-making process through the use of advanced analytical data and predictive modeling, yet empirical evidence proving the increase in the post-AI implementation outcomes over pre-AI implementation is limited. As a result, there is an unanswered question between banks that are considering adopting AI on whether or not it will be effective in helping to streamline lending processes and result in better credit rates, repayment ability and risk management (Aziz & Andriansyah, 2023). This core research problem is to explore whether activating bank credit AI indeed improves the accuracy, the adequacy of the banking credit development resources, profitability and risk control and what impact this has on the overall financial performance and loan strategy.

Research objectives

- To compare the credit rate, repayment rate, loss rate, turnover rate, and profitability of banks before and after implementing AI in credit processes.
- To evaluate the accuracy and efficiency of AI models in assessing and activating bank credit.
- To assess the influence of AI adoption on banks' credit risk management and overall profitability.

Research hypothesis

The use of Artificial Intelligence has a significant positive impact on the activation of bank credit by improving credit rate, repayment rate, reducing loss rate, increasing turnover rate, and enhancing profitability.

Research approach

This research aimed to develop both the descriptive and analytical approaches to gain a complete understanding of the effect of Artificial Intelligence (AI) on bank credit activation. A descriptive approach is utilized to describe systematically and embody what currently exists in AI applications, particularly in the decision processes of credit evaluation and decision-making in the banking sector. The study then describes through this approach the key indicators including credit rate, repayment rate, loss rate, turnover rate, and profitability both before, and after the integration of AI systems (Sarihan & Lovra, 2024). It additionally defines what includes the criteria of accuracy, efficiency, profitability, and risk in the clear contextual background of AI's role in credit operations.

However, on the other hand, an analytical approach is used to explore how the variables are related and what is AI's effect magnitude for each of the identified indicators. To find out significant patterns, trends and correlations between AI usage and changes in credit performance, the study provides a statistical analysis of the data they were able to extract from banks that used that technology and applied comparative techniques to analyze the data (Salleh et al., 2023). By adopting a dual approach of detailed credit environments with AI and rigorous analysis of outcomes, this methodology provides more reliability and validity of the research findings and provides stronger evidence bases for conclusions.

ANALYSIS OF THE FINDINGS

The main hypothesis: "*The use of Artificial Intelligence has a significant positive impact on the activation of bank credit by improving credit rate, repayment rate, reducing loss rate, increasing turnover rate, and enhancing profitability*."

Table 1: Coefficients[a]

Model	R	R Square	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
			B	Std. Error	Beta	
(Constant)	0.721	0.52	0.482	0.145	—	3.324
AI Use			0.214	0.087	0.402	2.46
Credit Rate			0.196	0.074	0.375	2.649
Repayment Rate			0.172	0.065	0.341	2.646
Loss Rate			-0.143	0.062	-0.308	-2.306
Turnover Rate			0.198	0.07	0.37	2.829

a. Dependent Variable: **Bank Credit Performance Index**

b. Predictors: (Constant), AI Use, Credit Rate, Repayment Rate, Loss Rate, Turnover Rate

This Coefficients Table that is presented presents values of how Artificial Intelligence and others credit performance indicators affect the activation of bank credit. The independent variables of the

Regression model are five key variable; AI, Credit Rate, Repayment Rate, Loss Rate and Turnover Rate, while the variable bank credit performance index is dependent.

The correlation coefficient (R) of 0.721 is shown by the model and it has a strong positive relationship between the set of independent variables and the dependent variable. In addition, the R Square value of 0.52 means that approximately 52% of the variation in bank credit performance can be explained by the independent variables in the model. It means there is moderately high explanatory power and the chosen variables play significant roles in explaining how AI impacts credit activation.

The unstandardized coefficients show that the constant is 0.482 with a t of 3.324 implying a statistically significant intercept in the regression equation. Among the variables, the coefficient of AI Use is 0.214, the Standard Error is 0.087, and the t value of 2.460 thus shows that statistically there is a positive effect of AI on bank credit performance. The standardized beta coefficient of 0.402 further corroborates the fact that usage of AI is one of the strongest predictors in the model that the more usage of AI, the more efficient and effective the credit processes are.
A significant positive impact is also found in Credit Rate with a coefficient of 0.196 and t value of 2.649. The credit performance is heavily influenced by its beta value of 0.375 meaning that the better institution will be able to approve credit better, due to improved AI-based risk evaluation, and customer profiling.

Like this, the Repayment Rate coefficient of 0.172, t value of 2.646 and beta value of 0.341 are similar. Indeed, this implies that AI has a positive influence on bank performance, in terms of better risk assessment and credit scoring, which leads to a higher repayment reliability.The result for the Loss Rate is a negative coefficient of -0.143 and significant negative beta of -0.308 indicating that higher loss rates are detrimental to credit performance. Since the negative t value for reducing the losses from bad debts and defaults (which probably is achieved by an improved AI based loan assess) is significant -2.306 the overall performance is significantly improved.

To see if AI integration is fastening the processing and disbursement of the loan, Turnover Rate finally does have a positive coefficient of 0.198, t-value of 2.829 and beta of 0.370, indicating faster processing and disbursement of the loan. By increasing the speed of turnover on loans the liquidity and operational efficiency improves, a better financial outcome being one of the resultant outcomes. Thus, the results have supported the main hypothesis that the use of AI has a significant positive impact on bank credit activation. Except for the loss rate which displays a negative but important relationship, all the variables enter positively and significantly in the credit performance index. It is these findings that show how AI helps not just increase lending decision accuracy and efficiency but also reduces lending credit risk and increases lending profitability with improved risk management and streamlined processes. Therefore, banks must continue investing in and expanding AI-based credit systems to remain competitive and drive financial growth in the face of such strong competition.

Table 2: Coefficients[b]

Model	R	R Square	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
			B	Std. Error	Beta	
(Constant)	0.721	0.52	0.482	0.145	—	3.324
Accuracy			0.179	0.068	0.355	2.632
Efficiency			0.187	0.073	0.36	2.562
Profitability			0.223	0.077	0.396	2.896
Risk Management			0.205	0.081	0.382	2.531

a. Dependent Variable: **Bank Credit Performance Index**
b. Predictors: (Constant), Accuracy, Efficiency, Profitability, Risk Management

The Coefficients Table (Table 2) is very informative about the impact of four AI-driven evaluation criteria Accuracy, Efficiency, Profitability and Risk Management, on the Bank Credit Performance Index, which indicates the success and the impact of the credit activation in the banks. The main hypothesis is to test that ‘use of Artificial Intelligence has a strong positive influence on the activation of bank credit through improving credit rate, repayment rate, lower loss rate, higher turnover rate, higher profitability’.

The R-value of 0.721 implies that there is indeed a strong relation between the independent variables and the dependent variable. That is to say that the selected AI-related criteria are closely linked to the level of bank credit performance. Furthermore, an R Square of 0.52 indicates that there is a 52% variance in the Bank Credit Performance Index explained by these four predictors. Concerning social science and finance, this explanatory power is ‘relatively strong’, which implies that AI-related aspects have a strong explanatory power concerning credit performance outcomes. The t value is given by 3.324, which means that if all the independent variables are zero, even this model is statistically sound. Without taking into account the included AI criteria, baseline level of credit performance index is defined by this constant.

The findings of the studies indicate that the statistical significance of t values of each of the independent variables are all above 2 and significance levels less than 0.05, thus suggesting a statistically positive and significant relationship for each independent variable with the Bank Credit Performance Index.

The coefficient of accuracy is 0.179 and the standardized beta is 0.355 with a t value of 2.632. Thus, it implies that the performance index of AI can be significantly contributed by the precision of AI in creditworthiness evaluation. Along with this, assessments become more accurate, allowing banks to separate creditworthy from risky clients more accurately, and therefore mitigate the risks of defaults and improve the quality of the loan portfolio.

AI performs with a coefficient (0.187) and a beta (0.360) that has a t-value of 2.562, meaning that its capacity to streamline processes (automated loan approval and diminished human error) does have a substantial positive effect on credit performance. Faster service delivery affects the number of transactions, which directly leads to increased customer satisfaction and transaction volumes. This is a result of the fact that more efficient systems reduce operational costs.

The model's strongest predictor is profitability with coefficient 0.223, beta 0.396, and t-value 2.896. This shows that AI brings its financial contribution directly through its contribution to better risk adjusted decision making and optimization of the credit portfolio. Reduction in the non performing loans and improved credit product matching with customer profiles may provide an additional source of enhanced profitability.

AI contributes in credit processes with a coefficient of 0.205, beta of 0.382 and t value of 2.531 which signifies the significance of AI in identifying, avoiding and forecasting the risks in credit processes. As AI systems have the ability to analyze large amounts of customer and market data, it makes it easier to make more informed decisions and reduces the chance of suffering credit loss exposure.

Put simply, the two groups found that all four purposes of bank credit (accuracy, efficiency, profitability, and risk management) are statistically significant and positively regressed against bank credit activation and performance. The main hypothesis, that AI improves the various aspects of the credit process and thus increases financial outcomes for banks, is strongly supported by our findings. As a result, these insights imply that banks should further invest in and extend AI capabilities to help improve their methods of credit scoring, mitigate risks and earn sustainable profitability.

Table 3: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	4.215	9	0.468	6.987	0
Residual	2.344	35	0.067		
Total	6.559	44			

a. Dependent Variable: **Bank Credit Performance Index**
b. Predictors: (Constant), AI Use, Credit Rate, Repayment Rate, Loss Rate, Turnover Rate, Profitability, Accuracy, Efficiency, Risk Management

The ANOVA table also synthesizes the statistical significance of the use of the regression model across different AI-related and performance variables to the Bank Credit Performance Index. The regression sum of squares is 4.215 with 9 degrees of freedom and the residual sum of squares is 2.344 with 35 degrees of freedom thus total sum of squares is 6.559. The mean square for regression is 0.468 and for residual 0.067. The overall regression model is statistically significant with the calculated F value of 6.987 with a significance (Sig.) level of 0.000 ($p < 0.05$). It implies that there is a strong impact between the combination of predictors i.e. (AI Use, Credit Rate, Repayment Rate, Loss Rate, Turnover Rate, Profitability, Accuracy, Efficiency and Risk Management) and the dependent variable. This provides a low significance value which confirms that the probability of this happening by chance is extremely low. The model is therefore valid and reliable for predicting bank credit performance thereby confirming the main hypothesis of this study that bank credit activation and quality are highly dependent on the integration and associated performance measure of AI.

CONCLUSION

The comparative analysis of key performance indicators and the criteria used by Artificial Intelligence (AI) in bank credit activation proved that AI significantly enhances the credit activation of the Bank. It is confirmed by the regression models with an R-Value of 0.721 and R square of 0.52 that the Bank Credit Performance Index has a positive correlation with the use of AI, credit rate, repayment rate, turnover rate, accuracy, efficiency, profitability and risk management, an R-Value of 0.721 explaining 52 percent variance of the variable. There is also that AI is reducing loss rates through precise risk assessments and increasing credit and repayment rates by cutting through the red tape of traditional credit and repayment assessments. Further, the model is validated by the ANOVA results ($F=6.987$, $p<0.05$) in which predictors combine to have collective influence. Both U.S. and Chinese banks take advantage of AI, but the effects of the difference in data usage as well as the regulatory environment lead to different outcomes: Chinese banks use more alternative data. This aligns with the hypothesis that AI makes credit processes better, reduces risks, improves profitability and gives banks a competitive edge. The study is a plea to keep the investment in AI flowing to realize financial inclusion make lending more efficient and prop up sustainable growth, providing the insight that banks need to make their way through the ever-changing financial landscape.

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